e_val_multi_group_model

April 28, 2020

0.1 Eigenvalue Change of Next Generation Matrix

Analytically derived a formula to predict the change in the largest eigenvalue of the next generation matrix when we remove one type of infected individual from a multi-group SIR model. This has importance as the largest eigenvalue/spectral radius of the next generation matrix gives the R_0 for the system.

If we consider **G** to be the next generation matrix for the entire multigroup model, with largest eigenvalue λ that has associated left and right eigenvectors \mathbf{v}^T and \mathbf{u} , then we define the relative importance of an infective node I_k to be

$$\mathcal{I}_k = -\frac{\Delta \lambda}{\lambda}$$

where $\Delta\lambda$ is the change in the largest eigenvalue upon removal of I_k from the system. We derived the following analytical approximation

$$\mathcal{I}_k = \frac{\mathbf{u}_k \mathbf{v}_k}{\mathbf{v}^T \mathbf{u} - \mathbf{u}_k \mathbf{v}_k}.$$

In this notebook, we will apply this approximation to a self-generated toy example.

0.1.1 The Model

Each state has an average transmission rate $B_i = \sum_{j=1}^{7} B_{j,i}$ which gives a rate at which state i infects the other states (including itself). We consider the following multi-group model:

$$\frac{dS_i}{dt} = -\sum_{i=0}^{7} B_{i,j} N_i I_j \tag{1}$$

$$\frac{dI_i}{dt} = \sum_{i=0}^{7} B_{i,j} S_i I_j - \gamma_i I_i \tag{2}$$

$$\frac{dR_i}{dt} = \gamma_i I_i \tag{3}$$

This system has a disease free solution, when $I_i = 0 \,\forall i$, and $S_i^* = \frac{\Lambda_i}{u_i}$.

0.1.2 Age Groups

62

0.27

0.30

0.13

Group data using pre-specified groups from PLOS data.

```
In [114]: import numpy as np
    import matplotlib.pyplot as plt
    import pandas as pd

matplotlib.rc('text', usetex=True)
    matplotlib.rcParams['text.latex.preamble']=[r"\usepackage{amsmath}"]
```

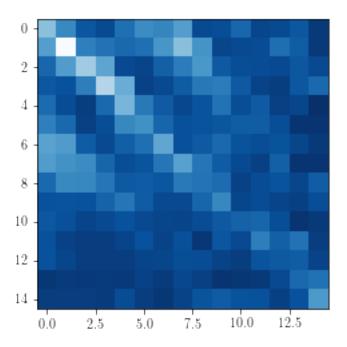
Importing Data from Contact Rate Paper Paper Reference: https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.0050074#s5 We specifically use data from the Table S8.4b), which we have converted into csv format.

```
In [557]: full_data = pd.read_csv("data/contact_data.csv", index_col=0)
          full_data
Out [557]:
                  2
                        7
                             12
                                    17
                                          22
                                                27
                                                       32
                                                             37
                                                                   42
                                                                          47
                                                                                52
                                                                                      57
                                                                                           \
                           0.25
              1.00
                    0.59
                                 0.18
                                        0.42
                                              0.61
                                                    0.57
                                                           0.74
                                                                 0.18
                                                                       0.20
                                                                              0.36
                                                                                    0.15
          7
              0.74
                    1.72
                          0.53
                                 0.44
                                        0.37
                                              0.42
                                                    0.68
                                                           0.99
                                                                 0.66
                                                                        0.15
                                                                              0.17
                                                                                    0.19
              0.36
                                              0.14
          12
                    0.73
                           1.09
                                 0.79
                                        0.17
                                                    0.32
                                                           0.51
                                                                 0.69
                                                                        0.27
                                                                              0.20
                                                                                    0.19
                     0.22
                           0.52
                                                           0.29
          17
              0.26
                                 1.20
                                        0.85
                                              0.12
                                                    0.17
                                                                 0.48
                                                                        0.51
                                                                              0.27
                                                                                    0.13
          22
              0.39
                    0.19
                           0.09
                                 0.38
                                        0.92
                                              0.49
                                                    0.28
                                                           0.16
                                                                 0.23
                                                                        0.44
                                                                              0.20
                                                                                    0.28
                                                                              0.30
          27
              0.53
                    0.37
                                              0.64
                                                    0.35
                                                                       0.25
                           0.11
                                 0.20
                                        0.58
                                                           0.21
                                                                 0.23
                                                                                    0.30
          32
              0.77
                    0.72
                          0.29
                                 0.17
                                        0.31
                                              0.42
                                                    0.80
                                                           0.21
                                                                 0.27
                                                                        0.38
                                                                              0.23
                                                                                    0.20
              0.73
                    0.65
                           0.61
                                 0.35
                                        0.20
                                              0.24
                                                    0.47
                                                           0.76
                                                                 0.47
                                                                        0.29
                                                                              0.18
          37
                                                                                    0.11
          42
              0.38
                    0.59
                           0.58
                                 0.47
                                        0.27
                                              0.29
                                                    0.25
                                                           0.49
                                                                 0.45
                                                                        0.40
                                                                              0.12
                                                                                    0.19
              0.22
                    0.23
                           0.22
                                 0.34
                                              0.29
                                                    0.17
                                                           0.17
                                                                        0.58
                                                                              0.15
          47
                                        0.46
                                                                 0.35
                                                                                    0.19
              0.26
                    0.21
                           0.14
                                 0.17
                                        0.22
                                                    0.15
                                                           0.14
                                                                 0.19
                                                                        0.27
                                                                              0.33
                                                                                    0.35
          52
                                              0.17
              0.22
                    0.12
                          0.10
                                 0.10
                                        0.14
                                              0.22
                                                    0.13
                                                           0.21
                                                                 0.05
                                                                        0.25
                                                                              0.17
                                                                                    0.52
          62
              0.22
                    0.15
                           0.10
                                 0.10
                                        0.10
                                              0.14
                                                    0.15
                                                           0.20
                                                                 0.19
                                                                        0.13
                                                                              0.09
                                                                                    0.24
              0.05
                    0.08
          67
                          0.07
                                 0.08
                                        0.07
                                              0.12
                                                    0.08
                                                           0.16
                                                                 0.11
                                                                        0.04
                                                                              0.05
                                                                                    0.07
          72
              0.09
                    0.09
                           0.10
                                 0.08
                                       0.19
                                              0.10
                                                    0.05
                                                           0.13
                                                                 0.24
                                                                        0.29
                                                                              0.23
                                                                                    0.22
                62
                       67
                             72
          2
                     0.26
              0.18
                           0.07
          7
              0.41
                     0.30
                           0.07
              0.17
                     0.26
          12
                           0.17
              0.09
                    0.26
          17
                          0.37
          22
              0.11
                     0.15
                          0.00
          27
              0.20
                    0.04
                          0.03
          32
              0.23
                    0.15
                          0.07
          37
              0.32
                     0.04
                           0.03
          42
              0.23
                    0.15
                          0.30
          47
              0.14
                    0.11
                           0.20
          52
              0.20
                    0.04 0.07
          57
              0.32
                    0.44
                          0.10
```

```
67 0.17 0.37 0.43
72 0.11 0.22 0.70
```

```
In [558]: age_range = [2,7,12,17,22,27,32,37,42,47, 52,57,62,67,"70+"]
```

Out[559]: <matplotlib.image.AxesImage at 0x140c414e9b0>

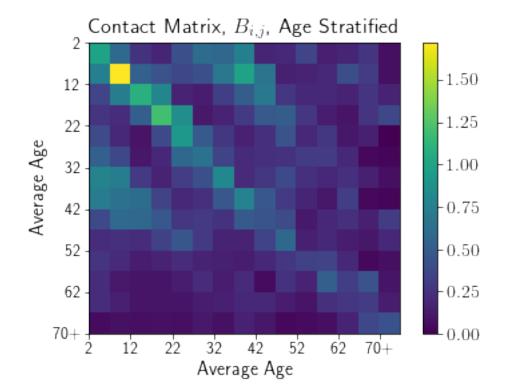


```
In [560]: plt.imshow(full_data, interpolation="nearest")
    x = np.arange(0,15,1) # the grid to which your data corresponds
    nx = x.shape[0]
    no_labels = 7 # how many labels to see on axis x
    step_x = int(nx / (no_labels - 1)) # step between consecutive labels
    x_positions = np.arange(-0.5,nx - 0.5,step_x) # pixel count at label position
    x_labels = x[::step_x] # labels you want to see

final_labels = []
    for idx in x_labels.astype(int):
        if idx == 15:
            final_labels.append(age_range[idx - 1])
        else:
            final_labels.append(age_range[idx])
    plt.xticks(x_positions, final_labels)
    plt.yticks(x_positions, final_labels)
```

```
plt.xlabel("Average Age", fontsize = 14)
plt.ylabel("Average Age", fontsize = 14)
plt.title("Contact Matrix, $B_{i,j}$, Age Stratified", fontsize = 16)
plt.xticks(fontsize=12, rotation=0)
plt.yticks(fontsize=12, rotation=0)
cbar = plt.colorbar()
cbar.ax.tick_params(labelsize=14)
```

#plt.savefig("imgs/contract_rate_matrix.pdf", bbox_inches = "tight")



```
# tempdata

# contact_data = np.zeros((5,5))

# cols = [2, 5, 8, 11, 14]
# count = 0

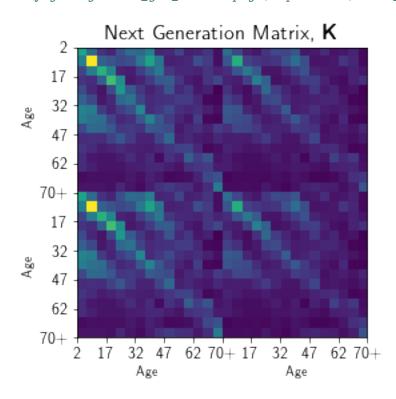
# for row in range(len(tempdata)):
# count = 0
# for col in cols:
# contact_data[row, count] = np.mean((tempdata[row, col], tempdata[row, col count+=1])

# plt.imshow(contact_data, cmap = "Blues_r")
```

0.2 Defining other model parameters

We need to define the following for the model: - The recovery rates of the fast and slow reporters. - The population of each type (we assume the same population level for each type, which appears to be realistic, https://www.statista.com/statistics/281174/uk-population-by-age/)

```
In [542]: # Slow reporters (gamma_1)
          gamma_1 = 0.5
          # Fast Reporters (gamma_2)
          gamma 2 = 0.8
          gamma = [gamma_1]*len(data) + [gamma_2]*len(data) # recovery rates for the 10 differ
In [543]: # generating the next generation matrix K
          K = np.zeros((len(data)*2,len(data)*2))
          for i in range(len(K)):
              for j in range(len(K)):
                  K[i,j] = data[i % len(data),j % len(data)] / gamma[j]
In [561]: plt.imshow(K, interpolation="none", extent=[0,30,30,0])
          plt.title("Next Generation Matrix, $\\textbf{K}$", fontsize = 16)
          x = \text{np.arange}(0,31,1) # the grid to which your data corresponds
          nx = x.shape[0]
          no\_labels = 10 # how many labels to see on axis x
          step_x = int(nx / (no_labels - 1)) # step between consecutive labels
          x_positions = np.arange(0,nx,step_x) # pixel count at label position
```

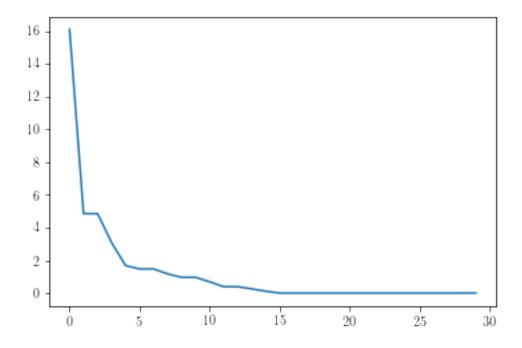


0.2.1 Finding the \mathcal{R}_0 of the model and eigenvalue decomposition.

```
In [545]: import scipy.linalg
     values, left, right = scipy.linalg.eig(K, right = True, left = True)
```

In [547]: plt.plot(values)

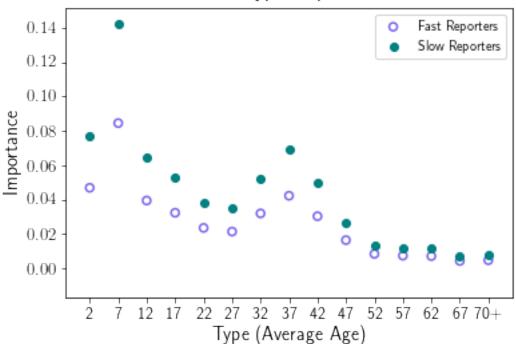
Out[547]: [<matplotlib.lines.Line2D at 0x140c2bba470>]



0.2.2 Type and Contact Importance

```
norm = lvec.dot(rvec)
              for i in range(len(lvec)):
                  arr.append((rvec[i]*lvec[i]) / (norm - lvec[i]*rvec[i]))
              return arr
In [549]: I_type = type_importance(K, lam, lvec, rvec)
In [562]: plt.scatter(range(len(I_type))[:len(data)], I_type[len(data):], marker = "o", faceco
          plt.scatter(range(len(I_type))[:len(data)], I_type[:len(data)], color = "teal")
          plt.title("Infectious Type Importance, $\mathcal{I}_k$", fontsize = 17)
          plt.ylabel("Importance", fontsize = 14)
          plt.xlabel("Type (Average Age)", fontsize = 14)
         plt.yticks(fontsize = 13)
          x = np.arange(0,15,1) # the grid to which your data corresponds
          nx = x.shape[0]
          no_labels = 9 # how many labels to see on axis x
          step_x = int(nx / (no_labels - 1)) # step between consecutive labels
          x_positions = np.arange(-0,nx - 0.5,step_x) # pixel count at label position
          x_labels = x[::step_x] # labels you want to see
          final_labels = []
          for idx in x_labels.astype(int):
              final_labels.append(age_range[idx])
          plt.xticks(x_positions, final_labels, fontsize = 12)
          plt.legend(["Fast Reporters", "Slow Reporters"])
          #plt.savefig("imgs/infectious_type.pdf", bbox_inches = "tight")
```

Infectious Type Importance, \mathcal{I}_k



no_labels = 10 # how many labels to see on axis x

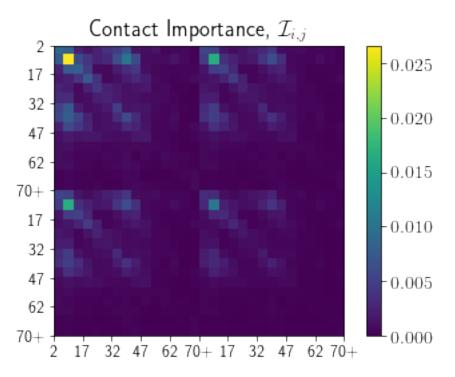
x = np.arange(0,31,1) # the grid to which your data corresponds

step_x = int(nx / (no_labels - 1)) # step between consecutive labels

In [564]: plt.imshow(I_contact)

nx = x.shape[0]

```
x_positions = np.arange(-0.5,nx -0.5,step_x) # pixel count at label position
x_labels = x[::step_x] # labels you want to see
x_labels = x_labels % 15
x_{labels}[5] = 15
x_{labels}[10] = 15
final_labels = []
for idk in x_labels:
    if idk == 15:
        final_labels.append(age_range[idk -1])
    else:
        final_labels.append(age_range[idk])
plt.xticks(x_positions, final_labels, fontsize = 12)
plt.yticks(x_positions, final_labels, fontsize = 12)
plt.title("Contact Importance, $\mathcal{I}_{i,j}$", fontsize = 17)
cbar = plt.colorbar()
cbar.ax.tick_params(labelsize=14)
#plt.savefig("imgs/contact_importance_png_version.png", dpi=600)
```

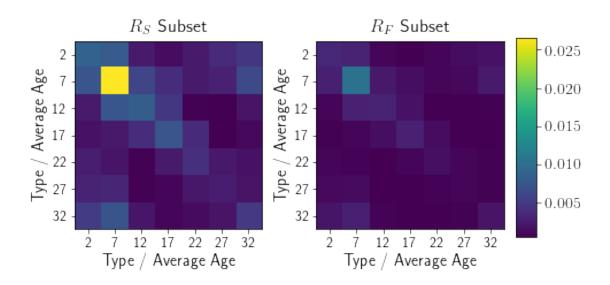


```
In [555]: I_1 = I_contact[:7, :7]

I_2 = I_contact[15:22, 15:22]
```

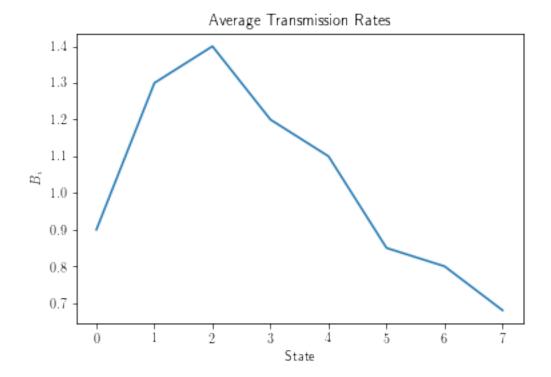
```
In [563]: import matplotlib.colors as colors
          import matplotlib
          import copy
          fig, (ax1, ax2) = plt.subplots(1,2)
          colormap = matplotlib.cm.viridis #or any other colormap
          normalize = matplotlib.colors.Normalize(vmin=np.min(I_1), vmax= np.max(I_1))
          im1 = ax1.imshow(I_1, cmap=colormap, norm=normalize)
          ax1.set_title("$R_S$ Subset", fontsize = 16)
          ax1.set_xlabel("Type / Average Age", fontsize = 14)
          ax1.set_ylabel("Type / Average Age", fontsize = 14)
          ax2.imshow(I_2, cmap=colormap, norm=normalize)
          ax2.set_title("$R_F$ Subset", fontsize = 16)
          ax2.set_xlabel("Type / Average Age", fontsize = 14)
          ax2.set_ylabel("Type / Average Age", fontsize = 14)
          cbar_ax = fig.add_axes([1.0, 0.2, 0.04, 0.6])
          cbar = plt.colorbar(im1, cax = cbar_ax)
          cbar.ax.tick_params(labelsize=14)
          final_labels = [2, 7, 12, 17, 22, 27, 32]
          locs = ax1.get_yticks()
          ax1.set_xticklabels( final_labels, fontsize = 12)
          ax1.set xticks(locs[1:-1])
          ax1.set_yticklabels([""] + final_labels, fontsize = 12)
          ax2.set_xticklabels( final_labels, fontsize = 12)
          ax2.set_xticks(locs[1:-1])
          ax2.set_yticklabels([""] + final_labels, fontsize = 12)
          plt.tight_layout()
```

 $\verb|C:\Anaconda3\lib\site-packages\ipykernel_launcher.py: 47: User \verb|Warning: This figure includes Axenda | Axe$

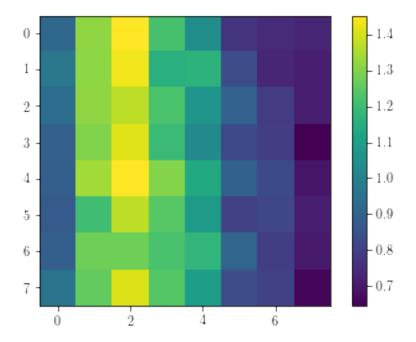


0.2.3 Second Example: Self-Generated Data

```
In [407]: # defining all parameters
          states = [0,1,2,3,4,5,6,7]
          average_transmission = [0.9, 1.3, 1.4, 1.2, 1.1, 0.85, 0.8, 0.68]
          mu = [1]*8
          Lambda = [1]*8
          Lambda[0] = 1.2
          gamma = 0.8 + 0.4*np.random.rand(8)
          # disease-free state values
          s_dfs = [0]*8
          for i in range(len(s_dfs)):
              s_dfs[i] = Lambda[i] / mu[i]
          plt.title("Average Transmission Rates")
          plt.ylabel("$B_i$")
          plt.xlabel("State")
          plt.plot(states, average_transmission)
          plt.show()
```



plt.show()



0.2.4 Next Generation Matrix

We obtain the next generation matrix **G** by first constructing two matrices **T** and Σ so that

$$\dot{\mathbf{x}} = (\mathbf{T} + \mathbf{\Sigma})\mathbf{x}$$
, where $\mathbf{x} = (I_1, I_2, ..., I_n)^T$.

The matrix **T** represents terms in the ODE system that contribute to the disease transmission; in our example

$$\mathbf{T} = \begin{bmatrix} B_{11}S_1^* & B_{12}S_1^* & \dots & B_{1n}S_1^* \\ \vdots & \ddots & & \vdots \\ B_{n1}S_n^* & \dots & & B_{nn}S_n^* \end{bmatrix}.$$

Likewise, the matrix Σ represents all non-disease related transmissions within the infectious subsystem. In our example, this is

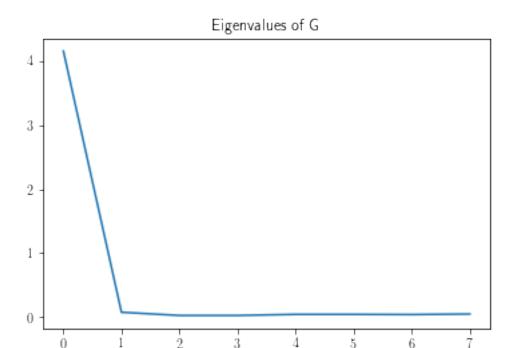
$$\Sigma = \begin{bmatrix} -(\gamma_1 + \mu_1) & 0 & \dots & 0 \\ 0 & -(\gamma_2 + \mu_2) & \dots & 0 \\ \vdots & \ddots & & \vdots \\ 0 & \dots & & -(\gamma_n + \mu_n) \end{bmatrix}.$$

Using the fact that $G=-T\Sigma^{-1}$, we have the next generation matrix:

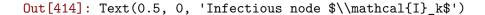
$$\mathbf{G} = \begin{bmatrix} \frac{B_{11}S_1^*}{\gamma_1 + \mu_1} & \frac{B_{12}S_1^*}{\gamma_2 + \mu_2} & \cdots & \frac{B_{1n}S_1^*}{\gamma_n + \mu_n} \\ \vdots & \ddots & & \vdots \\ \frac{B_{n1}S_n^*}{\gamma_1 + \mu_1} & \cdots & \frac{B_{nn}S_n^*}{\gamma_n + \mu_n} \end{bmatrix}.$$

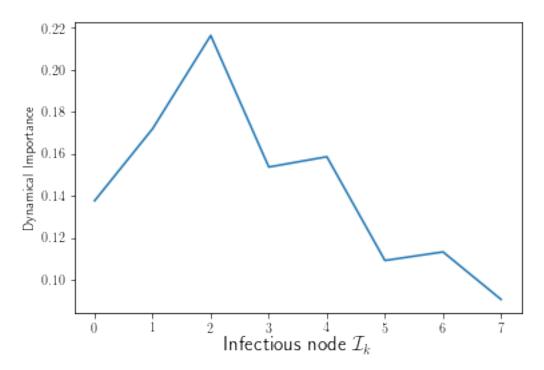
0.2.5 Infective State Importance

By computing eigenvectors and the largest eigenvalue of **G**, we can find an approximation to the importance of each infectious state.



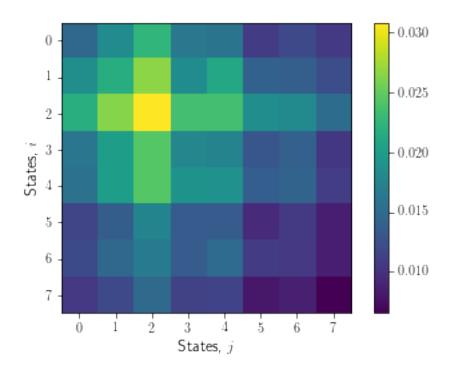
```
In [413]: # finding the important of each state from the eigenvalues and eigenvectors
          imp_list = []
          norm = abs(lvec.dot(rvec))
          print("Relative Importance of Infectious nodes for contribution to R_0:")
          for i in range(len(lvec)):
              imp = np.real(rvec[i]*lvec[i] / (norm - rvec[i]*lvec[i]))
              imp_list.append(imp)
              print("I_{{}}".format(i+1) + " = " + str(np.round(imp,2)))
Relative Importance of Infectious nodes for contribution to R_O:
I_1 = 0.14
I_2 = 0.17
I_3 = 0.22
I_4 = 0.15
I_5 = 0.16
I_6 = 0.11
I_7 = 0.11
I_8 = 0.09
In [414]: plt.plot(imp_list)
          plt.ylabel("Dynamical Importance")
          plt.xlabel("Infectious node $\mathcal{I}_k$", fontsize = 15)
          #plt.savefig("node_importance.pdf", bbox_inches = "tight")
```





0.2.6 Importance Matrix of the Contacts between the members of the population

C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: ComplexWarning: Casting complex values after removing the cwd from sys.path.



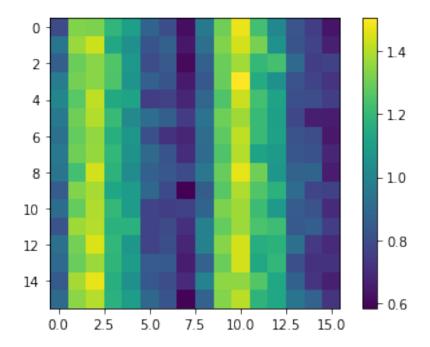
0.2.7 Extension, Male and Female Seperation without a Contact Matrix

```
In [26]: # defining all parameters
         states = list(range(16))
         average_transmission = [0.9, 1.3, 1.4, 1.2, 1.1, 0.85, 0.8, 0.68]*2
         mu = [1]*16
         Lambda = [1]*16
        Lambda[0] = 1.2
         Lambda[8] = 1.2
         gamma_1 = 0.9 + 0.4*np.random.rand(8) # slow responders
         gamma_2 = 0.6 + 0.2*np.random.rand(8) # fast responders
         gamma = np.concatenate((gamma_1, gamma_2))
         # disease-free state values
         s_dfs = [0]*16
         for i in range(len(s_dfs)):
             s_dfs[i] = Lambda[i] / gamma[i]
         # plt.title("Average Transmission Rates")
         # plt.ylabel("B_i")
         # plt.xlabel("State")
         # plt.plot(states, average_transmission)
         # plt.show()
```

```
In [27]: # generating the actual transmission rates
# sampling from a normal distribution w/ mean of the transmisson rates and a std of O
```

```
B = np.zeros((16,16))
for i in range(16):
    mean = average_transmission[i]
    for j in range(16):
        B[j,i] = 0.05*np.random.randn() + mean

plt.imshow(B)
plt.colorbar()
plt.show()
```



In [28]: # Generating the Next Generation Matrix

```
T = np.zeros((16,16))
Sigma = np.zeros((16,16))

for i in range(16):
    for j in range(16):
        T[i,j] = B[i,j]*s_dfs[i]
        if i ==j:
            Sigma[i,j] = -(gamma[i] + mu[i])

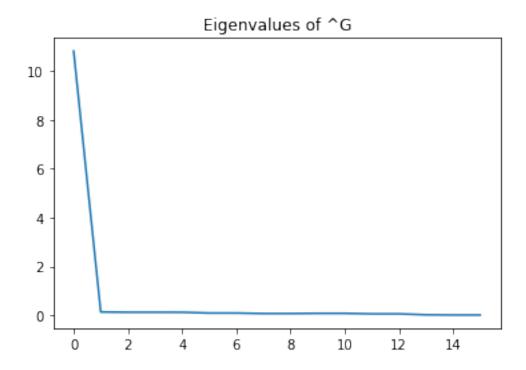
G = -T.dot(np.linalg.inv(Sigma))
```

```
In [29]: import scipy.linalg
    values, left, right = scipy.linalg.eig(G, right = True, left = True)
    values = np.abs(values)

# l_e- largest eigenvalue
    # lvec - corresponding left eigenvector
# rvec - corresponding right eigenvector
l_e = values[0]
lvec = left[:, 0]
rvec = right[:, 0]

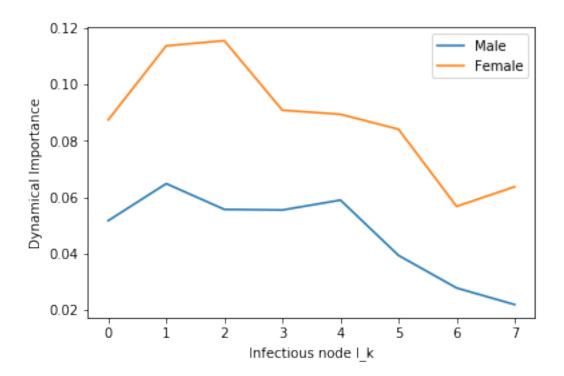
print("The Largest Eigenvalue of the Matrix is: " + str(np.round(l_e,2)))
plt.plot(values)
plt.title("Eigenvalues of `G")
plt.show()
```

The Largest Eigenvalue of the Matrix is: 10.82

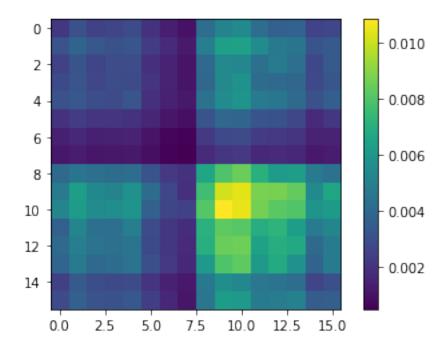


In [30]: # finding the important of each state from the eigenvalues and eigenvectors
 imp_list = []
 norm = abs(lvec.dot(rvec))
 print("Relative Importance of Infectious nodes for contribution to R_0:")

```
for i in range(len(lvec)):
             imp = np.real(rvec[i]*lvec[i] / (norm - rvec[i]*lvec[i]))
             imp_list.append(imp)
             print("I_{{}}".format(i+1) + " = " + str(np.round(imp,2)))
Relative Importance of Infectious nodes for contribution to R_0:
I_1 = 0.05
I_2 = 0.06
I_3 = 0.06
I 4 = 0.06
I_5 = 0.06
I_6 = 0.04
I_7 = 0.03
I_8 = 0.02
I_9 = 0.09
I_10 = 0.11
I_11 = 0.12
I_12 = 0.09
I_13 = 0.09
I_14 = 0.08
I_15 = 0.06
I_16 = 0.06
In [31]: plt.plot(imp_list[:8])
         plt.ylabel("Dynamical Importance")
         plt.xlabel("Infectious node I_k")
         plt.plot(imp_list[8:])
         plt.legend(["Male", "Female"])
Out[31]: <matplotlib.legend.Legend at 0x1531c358da0>
```



C:\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: ComplexWarning: Casting complex values after removing the cwd from sys.path.



In []: